

Exact Acceleration of Linear Object Detectors



Charles Dubout
François Fleuret

Idiap Research Institute

9 October 2012

Plan

Architecture of a modern linear object detector

- The sliding window technique
- HOG and linear SVM
- HOG feature planes

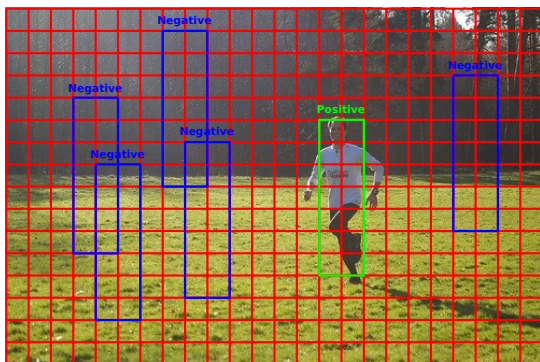
Deformable part-based models (DPM)

- DPM use a lot of filters
- Challenge

Our contribution

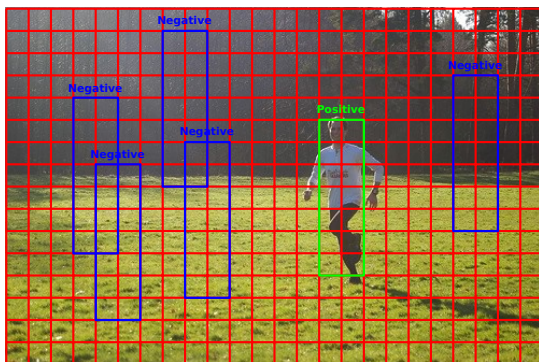
- Standard and Fourier convolution processes
- Patchworks of pyramid scales
- Cache violations
- Results

The sliding window technique



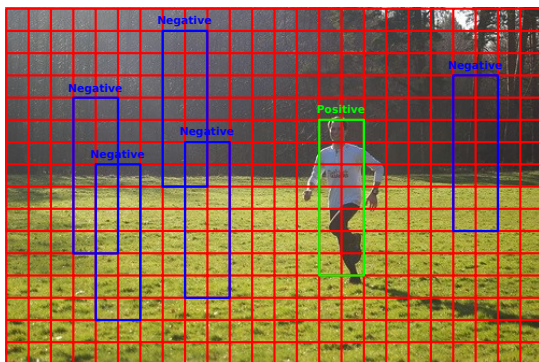
- Transforms a detection problem into a binary classification one

The sliding window technique



- Transforms a detection problem into a binary classification one
- Applies a binary classifier at every image position and scale

The sliding window technique

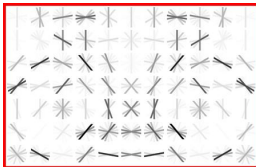


- Transforms a detection problem into a binary classification one
- Applies a binary classifier at every image position and scale
- Similar to sweeping the detection window across the whole image

Pedestrian template

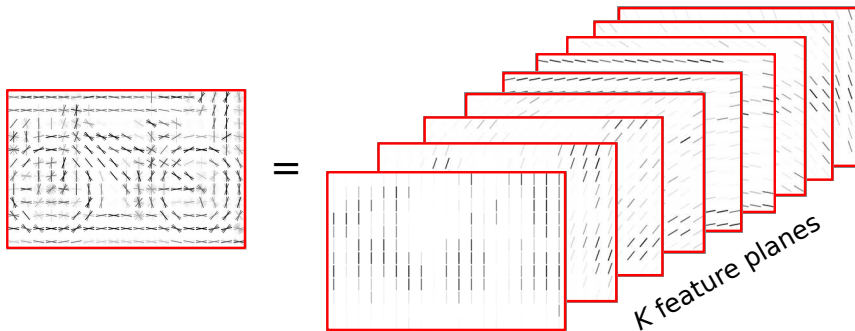


Bicycle template



Objects are image positions on the HOG grid: $score_{\mathbf{w}}(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle$,
where \mathbf{x} is the vector of features extracted from the subwindow at the
position of interest of size same as \mathbf{w} .

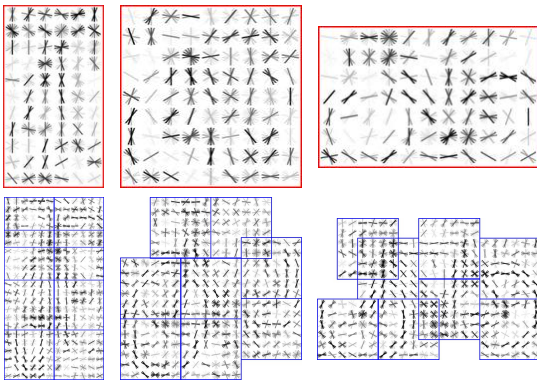
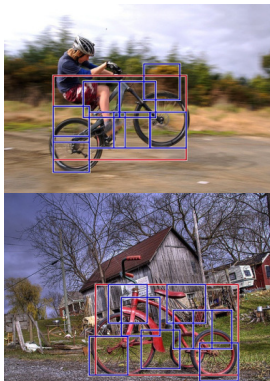
HOG feature planes



The HOG features can be seen as organized in planes, containing distinct features from each grid cell.

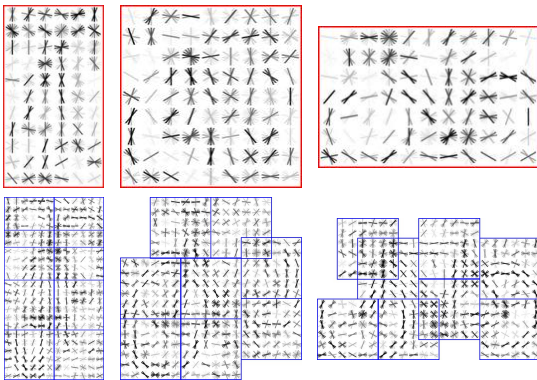
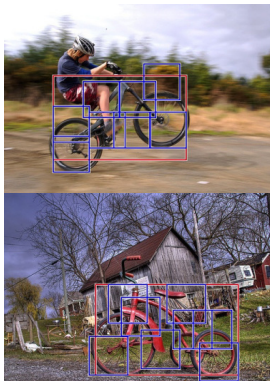
DPM* use a lot of filters

*Felzenszwalb & al. '08



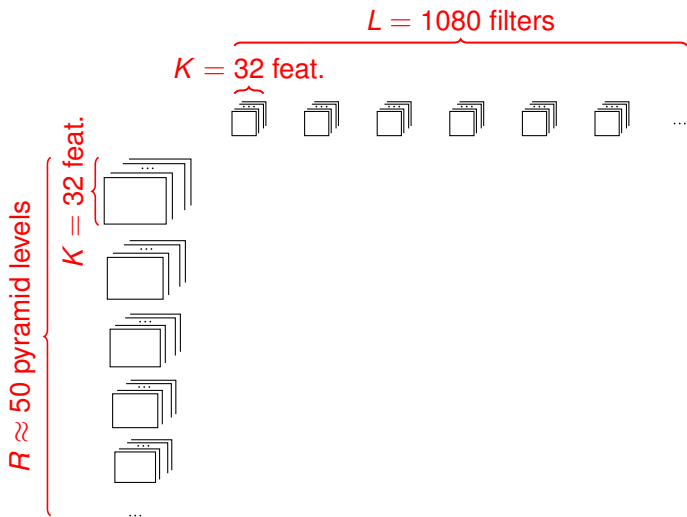
DPM* use a lot of filters

*Felzenszwalb & al. '08

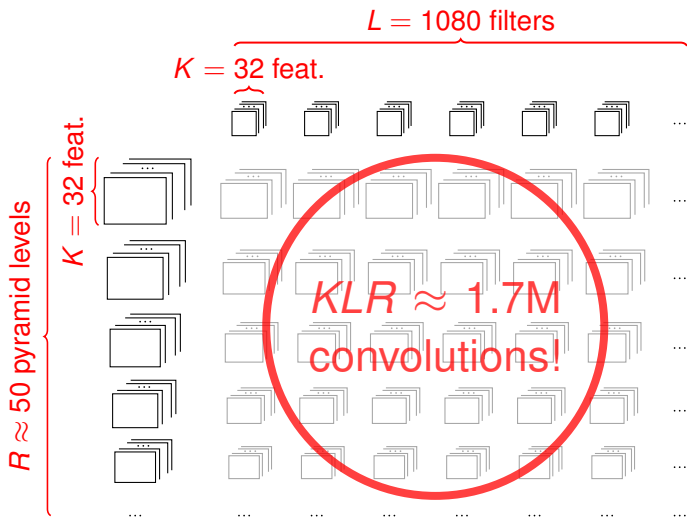


Typical numbers of filters used on the Pascal challenge:
20 classes \times 6 mixtures \times 9 parts = **1080 linear filters!**

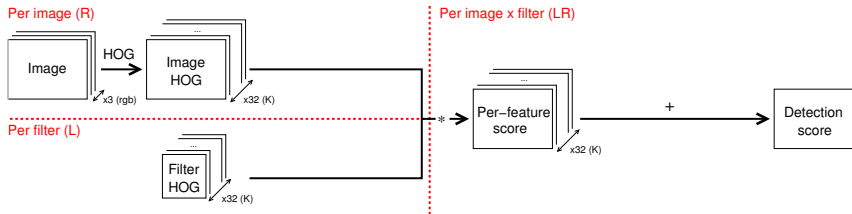
Challenge



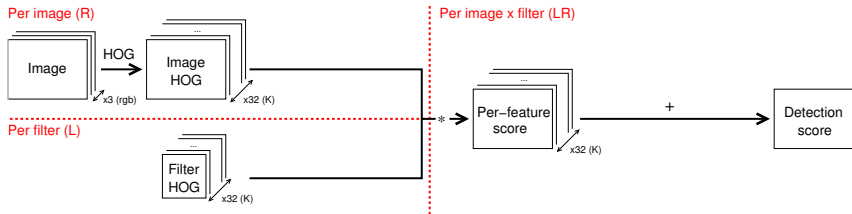
Challenge



Standard convolution process



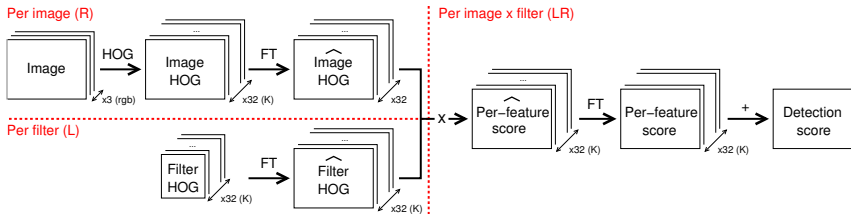
Standard convolution process



The computational cost to convolve a HOG image of size $M \times N$ with L filters of size $P \times Q$ across K features is:

$$C_{\text{std}} = \mathcal{O}(KLMNPQ)$$

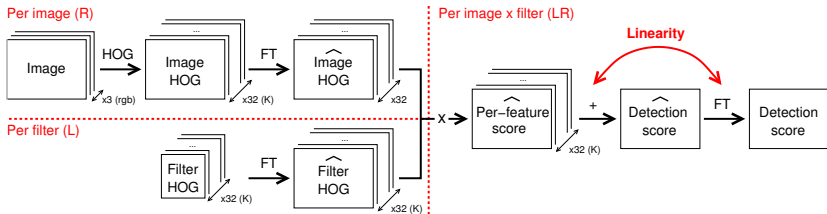
Fourier based convolutions



The computational cost to convolve a HOG image of size $M \times N$ with L filters of size $P \times Q$ across K features is:

$$C_{\text{FFT}} = \underbrace{\mathcal{O}(KMN \log MN)}_{\text{Forward FFTs}} + \underbrace{\mathcal{O}(KLMN)}_{\text{Multiplications}} + \underbrace{\mathcal{O}(KLMN \log MN)}_{\text{Inverse FFTs}}$$

Fourier based convolutions



The computational cost to convolve a HOG image of size $M \times N$ with L filters of size $P \times Q$ across K features is:

$$C_{\text{opt}} = \underbrace{O(KMN \log MN)}_{\text{Forward FFTs}} + \underbrace{O(KLMN)}_{\text{Multiplications}} + \underbrace{O(\cancel{K}LMN \log MN)}_{\text{Inverse FFTs}}$$

$$\approx O(KLMN)$$

Lets plug in typical numbers

- $K = 32$ (number of HOG features)
- $L = 54$ (number of filters)
- $M \times N = 64 \times 64$ (size of the pyramid level)
- $P \times Q = 6 \times 6$ (size of the filters)

Lets plug in typical numbers

- $K = 32$ (number of HOG features)
- $L = 54$ (number of filters)
- $M \times N = 64 \times 64$ (size of the pyramid level)
- $P \times Q = 6 \times 6$ (size of the filters)

$$C_{\text{std}} \approx 2KLMNPQ \approx 490 \text{ MFlop}$$

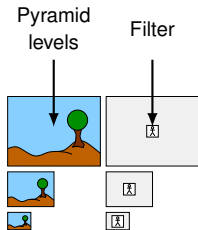
$$C_{\text{FFT}} \approx 3KLMN + 2.5(K + KL)MN \log_2 MN \approx 230 \text{ MFlop}$$

$$C_{\text{opt}} \approx 4KLMN + 2.5(K + L)MN \log_2 MN \approx 37 \text{ MFlop}$$

A gain by a factor **13** compared to the standard process,
and **6** compared to the standard Fourier one!

Patchworks of pyramid scales

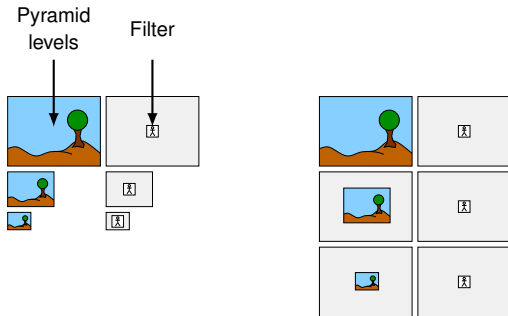
To use the FFT the image and the filter need to be of the same size.



Memory inefficient

Patchworks of pyramid scales

To use the FFT the image and the filter need to be of the same size.

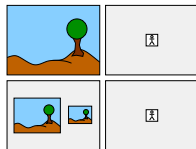
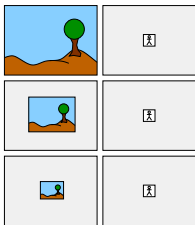
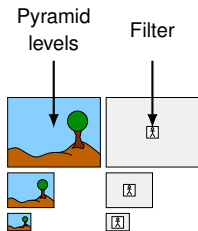


Memory inefficient

Computationally inefficient

Patchworks of pyramid scales

To use the FFT the image and the filter need to be of the same size.



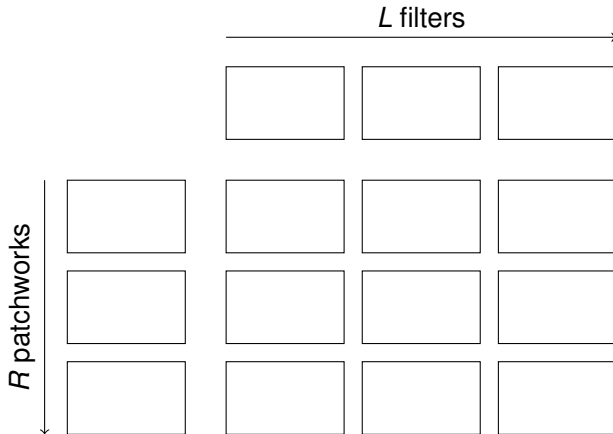
Memory inefficient

Computationally inefficient

Best of both worlds

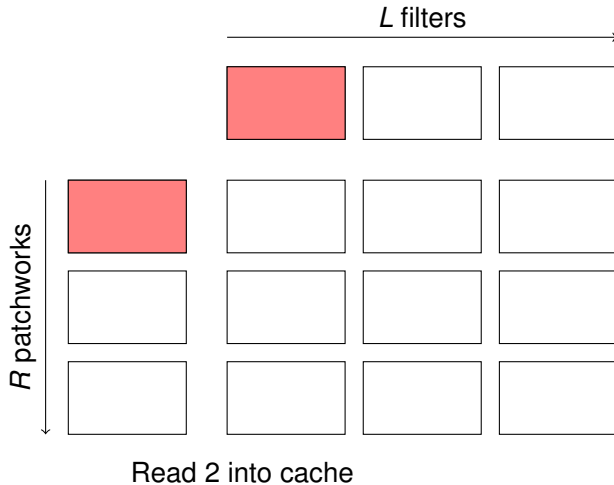
Cache violations

Naive strategy



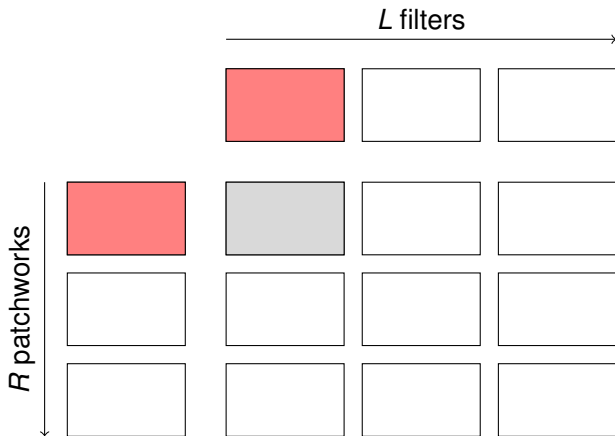
Cache violations

Naive strategy



Cache violations

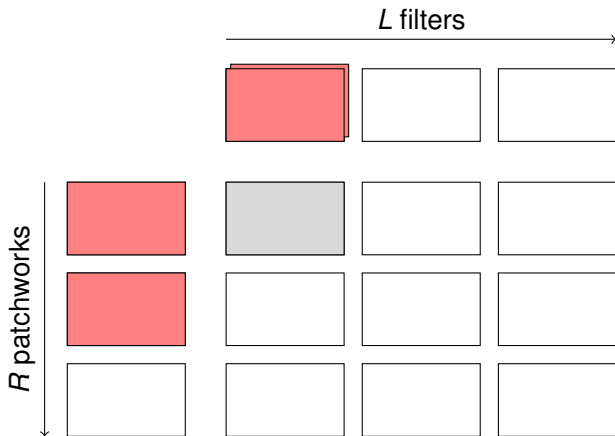
Naive strategy



Read 2 into cache \Rightarrow compute 1.

Cache violations

Naive strategy



Read 2 into cache \Rightarrow compute 1.

Cache violations

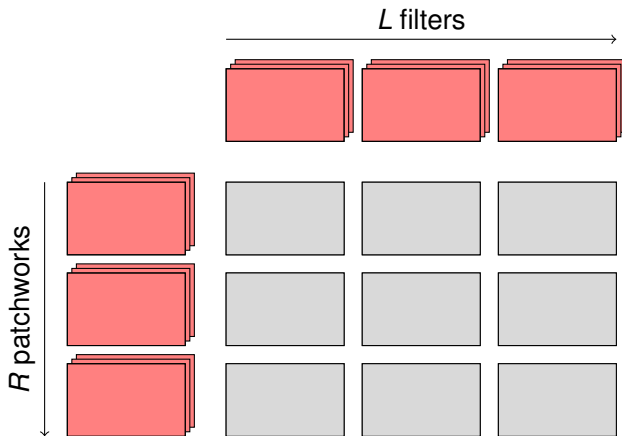
Naive strategy



Read 2 into cache \Rightarrow compute 1.

Cache violations

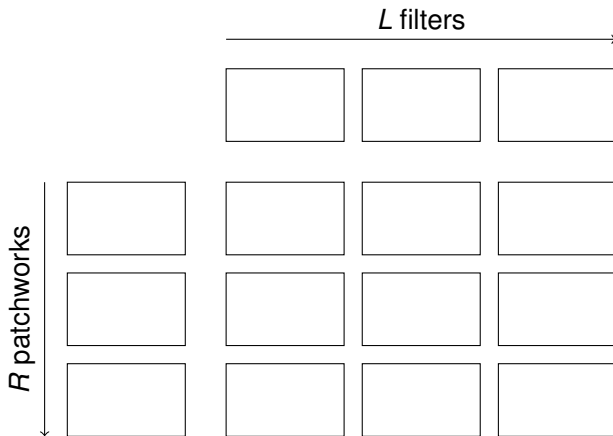
Naive strategy



Read $2LR$ into cache \Rightarrow compute LR .

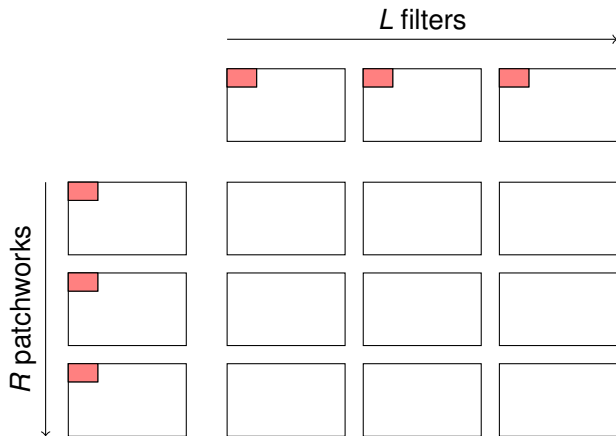
Cache violations

Fragment strategy



Cache violations

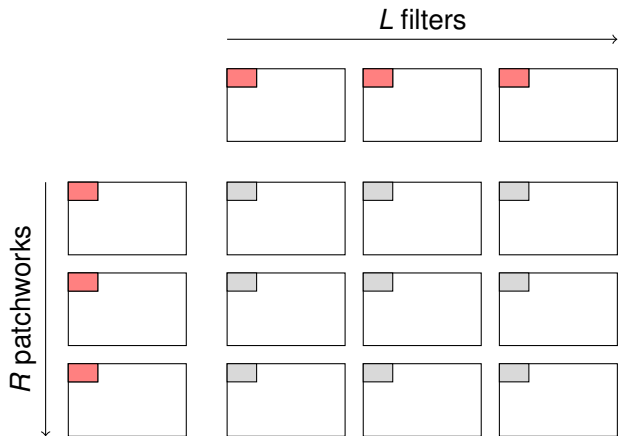
Fragment strategy



Read $(L + R) \frac{\epsilon}{L+R} = \epsilon$ into cache

Cache violations

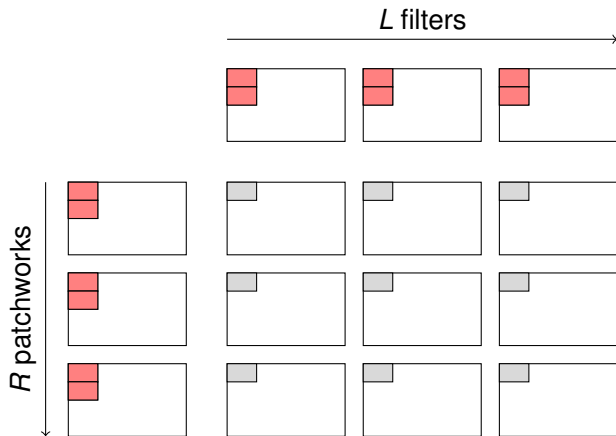
Fragment strategy



Read $(L + R) \frac{\epsilon}{L+R} = \epsilon$ into cache \Rightarrow compute $LR \frac{\epsilon}{L+R}$.

Cache violations

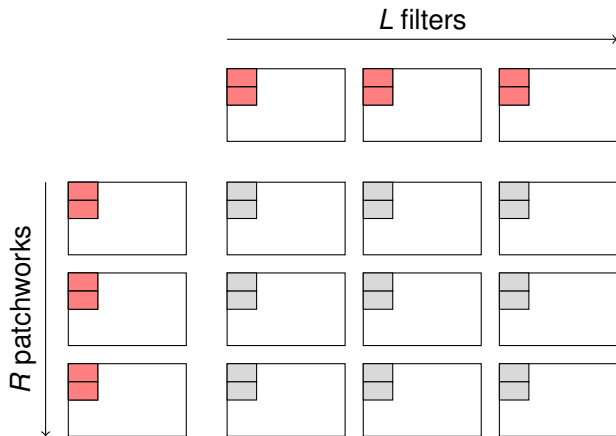
Fragment strategy



Read $(L + R) \frac{\epsilon}{L+R} = \epsilon$ into cache \Rightarrow compute $LR \frac{\epsilon}{L+R}$.

Cache violations

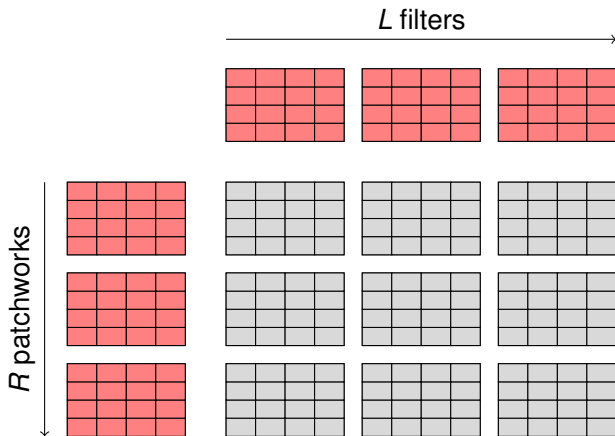
Fragment strategy



Read $(L + R) \frac{\epsilon}{L+R} = \epsilon$ into cache \Rightarrow compute $LR \frac{\epsilon}{L+R}$.

Cache violations

Fragment strategy



Read $L + R$ into cache \Rightarrow compute LR .

Results

Table : Pascal VOC 2007 challenge convolution time and speedup

	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table
V4 (ms)	409	437	403	414	366	439	352	432	417	429	450
Ours (ms)	55	56	53	56	57	56	54	56	56	57	57
Speedup (x)	7.4	7.8	7.6	7.4	6.4	7.9	6.5	7.7	7.5	7.5	8.0

	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
V4 (ms)	445	439	429	379	358	351	425	458	433	413
Ours (ms)	57	59	57	54	54	55	57	58	55	56
Speedup (x)	7.8	7.5	7.6	7.0	6.6	6.4	7.4	7.9	7.9	7.4

Results

Table : Pascal VOC 2007 challenge convolution time and speedup

	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table
V4 (ms)	409	437	403	414	366	439	352	432	417	429	450
Ours (ms)	55	56	53	56	57	56	54	56	56	57	57
Speedup (x)	7.4	7.8	7.6	7.4	6.4	7.9	6.5	7.7	7.5	7.5	8.0

	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
V4 (ms)	445	439	429	379	358	351	425	458	433	413
Ours (ms)	57	59	57	54	54	55	57	58	55	56
Speedup (x)	7.8	7.5	7.6	7.0	6.6	6.4	7.4	7.9	7.9	7.4

- Error rate: identical to the baseline (32.3% AP)

Results

Table : Pascal VOC 2007 challenge convolution time and speedup

	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table
V4 (ms)	409	437	403	414	366	439	352	432	417	429	450
Ours (ms)	55	56	53	56	57	56	54	56	56	57	57
Speedup (x)	7.4	7.8	7.6	7.4	6.4	7.9	6.5	7.7	7.5	7.5	8.0

	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
V4 (ms)	445	439	429	379	358	351	425	458	433	413
Ours (ms)	57	59	57	54	54	55	57	58	55	56
Speedup (x)	7.8	7.5	7.6	7.0	6.6	6.4	7.4	7.9	7.9	7.4

- Error rate: identical to the baseline (32.3% AP)
- Numerical accuracy: better than the baseline ($1.8 \cdot 10^{-8}$ vs. $2.4 \cdot 10^{-8}$ MAE)

Conclusion

- Part-based models obtain state-of-the-art performance at the price of a huge number of convolutions
- The FT is linear, enabling one to do the addition of the convolutions across feature planes in Fourier space
- The computational cost becomes invariant to the filters' sizes, resulting in a big speedup ($\times 7.4$ in our experiments, even more for bigger filters)

Exact Acceleration of Linear Object Detectors

Charles Dubout & François Fleuret

Idiap Research Institute

Thank you for your attention!

Questions?



Contact me at `charles.dubout@idiap.ch`